1 Type of bias – 1) Constraint
2) Preferences.

Bias means inclination for or against one group, especially in a way considered to be unfair.

Suppose 4 features and boolean value features

$$\overbrace{x_1 \quad x_2 \quad x_3 \quad x_4}^{\text{boolean values}}$$

Possible instance $\rightarrow 2^4 = 16$

How many boolean function possible?

- Number of functions means number of possible subsets of 16 instances.

i.e. $2^{16} / 2^{2^4}$.

For N, then 2^N.

So, it is not possible to check all the hypothesis.

Therefore we put restriction on hypothesis space.

- So, we select a hypothesis language.
- Hypothesis language reflect a bias (or inductive bias in the learner)

Inductive Bias —

- Need to make assumptions.
  - Experience alone doesn't allow us to make conclusions about unseen data instances.
- Two type of bias.
  - Restrictions – Limit the hypothesis space. (specifying form of a function 4th degree polynomial)
  - Preferences – Impose ordering on hypothesis space. (I am considering all possible polynomial, but I want low degree polynomial)

So we put bias in the training set.

Inductive learning —

- Inducing a general function from training examples.
  - Construct hypothesis h to agree with concept c on training examples.
  - A hypothesis is consistent if it agree with all training examples.
  - A hypothesis said to be generalized well if it correctly predicts the value of y for novel examples.
  - Generalization is important, generalized on training set as well as test set.

Inductive Learning is an ill Posed problem –
Unless we see all possible examples the data is not sufficient for an inductive learning algorithm to find a unique solution.

Inductive Learning Hypothesis –
- Any hypothesis h found to approximate the target function c well over a sufficiently large set of training example D will also approximate the target function well over other unobserved examples.

Note – By deciding a hypothesis, we impose a bias. (incorrect assumption)
So errors due to incorrect assumption or restriction on hypothesis space, error known as bias error.
Variance error is introduced when you have a small test set so variance error means the model that we estimate from different training sets will differ from each other. Suppose, we have 50 training set, we come up with 50 data point. ~~Bob a~~ After that we get another 50 data point which is from another distribution So, the variance from one set of data points to other set is called, variance bias.

Underfitting and Overfitting –
Underfitting – Model is too "simple" to represent all the relevant class characterstics.
- High bias and low variance.
- High training error and high test error.

Overfitting – Model is too "complex" and fits irrelevant characterstics (noise) in the data.
- Low bias & high variance.
- Low training error & high test error.

(3)

Hypothesis Space and Inductive Bias.

Inductive learning / Prediction -

Given example $(\hat{x}, y)$ or $(\hat{x}, f(x))$

- where x for a particular instance x comprises of the value of the different features of that instances and y is the output attribute.
- So if we assume that the output of an instance is a function of input vector (input feature vector), and $f(x)$ is the function that we ~~are~~ are trying to learn.

Supervised learning — [Classification, $f(x)$ is discrete. / Regression, $f(x)$ is continuous]

Probability estimation, $f(x)$ = Probability of $\hat{x}$

Type of Inductive learning - i) Classification ii) Regression iii) Probability estimation

Why this is called Inductive learning?

- We are given some data and we are trying to do induction to try to identify a function, which can explain the data.
- So induction as oppose to deduction, unless we can see all the instances / all the possible or we make some restrictive assumptions about the languages in which the hypothesis is expressed or some bias, this problem is not well defined so that is why it is called an inductive problem.

Feature, If we have to learn function, it should be function (features)

Instances are described in term of features. $f(\text{features})$.

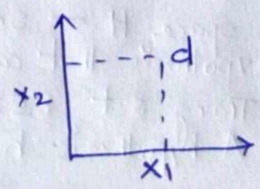
Features → Properties describe each Instance.

Feature vector → Multiple feature.

suppose 10 features, then feature vector will be 1 dimensional with 10 features.

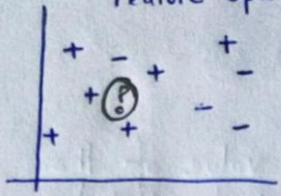
If we have n features, we can have n-dimension.

suppose, $d \Rightarrow x_1 = 2,\ x_2 = 5$

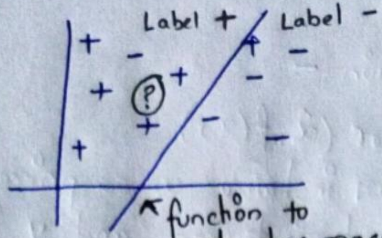


2 dimension

Feature Space.



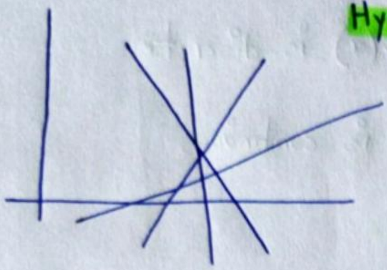
step 1



step 2.

So ?, will be positive

In cases, we can have multiple seperation



Hypothesis space – Set of legal hypothesis.
- We first defined the hypothesis space that is class of function that we are going to consider then given the data points, we try to come up with best hypothesis given data.

Hypothesis space → Based on features & language we can decide our hypothesis space.

So once we have chosen the features and the language or class of function what we have is hypothesis space.

H → hypothesis space (All possible output) h → learning algo output. (based on data, it will come up with one algo)

$h \in H$

Terminology –

Example $(\underset{i/p}{x}, \underset{o/p}{y})$ – Instance x with label $y = f(x)$.

Training data S – Collection of example observed by learning algorithm. (Input to the)

Instance space X – Set of all possible objects describable by features.

Concept c – Subset of objects from X (c is unknown) & $c \subseteq X$ (Suppose + and –, so $+ \subseteq X$ and $- \subseteq X$)

Target function f – Maps each instances $x \in X$ to target label $y \in Y$.

Classifier –

Hypothesis h – Function that approximates f.

Hypothesis space H – Set of functions we allow for approximating f.
- Set of hypothesis that can be produced, can be restricted further by specifying a language bias. (any bias)

Input – Traing set $S \subseteq X$.

Output – A hypothesis $h \in H$. that approximate f.